Department of Computer Science and Engineering
Indian Institute of Technology, Kharagpur

Complete The Look Recommendation with Street Fashion Images

Bhaskar Bagchi
bagchi.bhaskar@cse.iitkgp.ernet.in

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Content

- Given an item(clothing) in the shopping cart the problem statement is to suggest items complementary to it which may contain garments or accessories which makes a complete set as per current fashion.

Introduction
Problem Definition

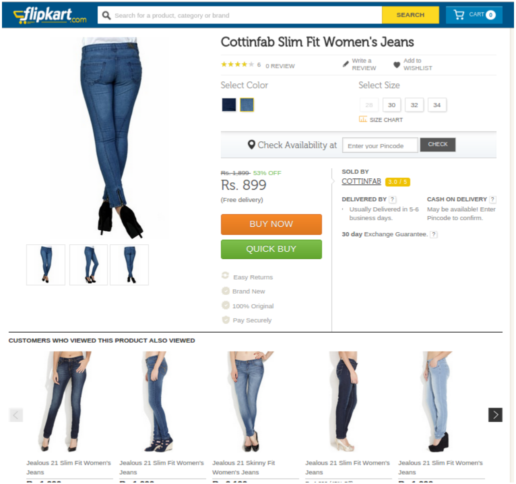

Figure: Existing Recommendation Systems

Introduction
Problem Definition

Figure: Visualization of the problem statement

Mathematical Formulation

Given an image i containing 'k' part–features, we describe the image P_i as $P_i^T := [p_{i1}, p_{i2}, ..., p_{ik}]$ where each p_{ij} are textual part–features, which are 2–tuples.

Mathematical Formulation

We learn a model from our dataset of fashion images, say **P**, where **P** := $[P_1, P_2, ...P_n]^T$.

Mathematical Formulation

The task of our recommendation system is, given one or more apparel, and corresponding part features *p*'s as input query, recommend garments which can be worn with it/them as a set.

Approach
Flow Diagram

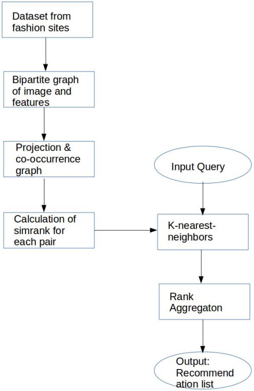

Figure: Flow Diagram of Proposed Approach

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- Created a vocabulary of part features. Manually normalize the tags associated with each image.
- Ended up with a codebook of total of *48* unique categories including garments like tops, jeans, etc. and accessories like watches, bracelets, etc. and *632* unique items i.e. category-description pair.

Bipartite Network and Co–occurrence Graph

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- The projected graph so obtained is a weighted co–occurrence graph of the part features. Construction of this graph gives us the relation between different garments and accessories which can be used together and are complementary to each other.
- This step helps us learn a correlation and inter-dependence between various part features from the dataset.

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- Convert the co–occurrence graph into a directed graph where each edge between part features p_a and p_b in the original graph is replaced by two directed edges $p_a \rightarrow p_b$ and $p_b \rightarrow p_a$ both with weights equal to the weight of original edge.

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- Compute *Simrank* between each pair of nodes.

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Similarity Measure & Nearest Neighbor

Nearest Neighbor Consensus

- Given a part–feature *p* as query we locate the node corresponding to that part feature in the co–occurrence graph.
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- The rationale behind this step is that since the graph had edges between part features that were used together by fashionistas and as the simrank values decrease with increase in node distances, the *k*–nearest–neighbors will be those part features which were frequently used with the selected item and are contemporary to it.

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- We get a list of k part features $p_1, p_2, ...p_k$ which are structurally close to the input feature and thus they can be recommended for the given query part feature.

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- Assigns a score corresponding to position in which a part feature appears within each ranked list. In our case, for each list i, ${p_a}^i$ is assigned a weight ${B_{p_a}}^i = k$ * fraction of part features in the list appearing below p_a.

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- The *Broda* score of each element B_{p_a} is the the sum of *Broda* scores for that part feature in all the lists.

Aggregating Ranked Item Recommendations
Rank Aggregation

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- The *Broda* score of each element B_{p_a} is the the sum of *Broda* scores for that part feature in all the lists.
- We can recomment the top k elements from this ranked list to the user.

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Experimental Results
Evaluation Methodology

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Formula

$$precision = \frac{no\ of\ matched\ recommendations}{no\ of\ recommendations}$$

$$recall = \frac{no\ of\ matched\ recommendation}{no\ of\ items\ in\ actual\ image}$$

Experimental Results
Results

Out of the 158 recommendation sets that we tested, 53 were 1 part feature input, 54 were 2 part feature input and 51 as 3 part feature input. For each generated recommendations we calculated the precision and recall.

Table: Precision

No. of inputs	Max Precision	Avg Precision
1	1	0.31
2	0.75	0.31
3	0.6	0.28

Table: Recall

No. of inputs	Max Recall	Avg Recall
1	0.8	0.23
2	1	0.44
3	1	0.48

Table: f1 score

No. of inputs	Max f1	Min f1
1	0.89	0.13
2	0.71	0.1
3	0.67	0.1

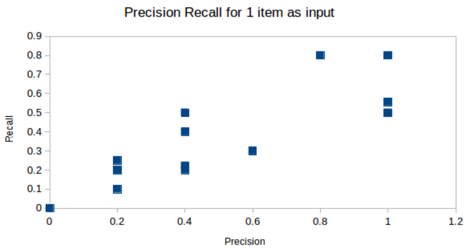
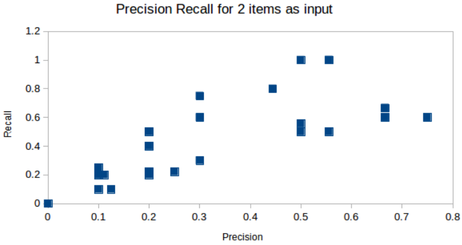


Figure: Precision-Recall for 1 item input

Experimental Results
Precision Recall Graphs



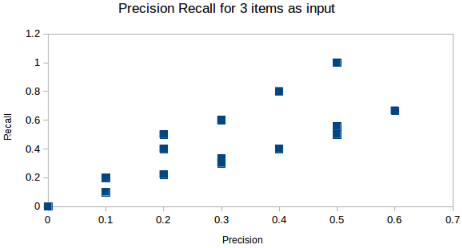


Table: User rating for recommendation

Rate(out of 10)	Frequency	Cumulative Freq.
10	1	1
9	2	3
8	9	12
7	9	21
6	5	26
5	11	37
4	11	48
3	6	54
2	4	58
1	2	60

Future Work

- Features for representation of parts are to be improved by incorporating visual features. Inclusion of visual features will also include the analysis of features like color, texture, etc. which is expected to improve the quality of evaluation.
- A feedback system can be added to the system as to increase edge weights to the features which are shopped together by users. This will be a self learning system and incorporate the changes in trending fashion all by itself.

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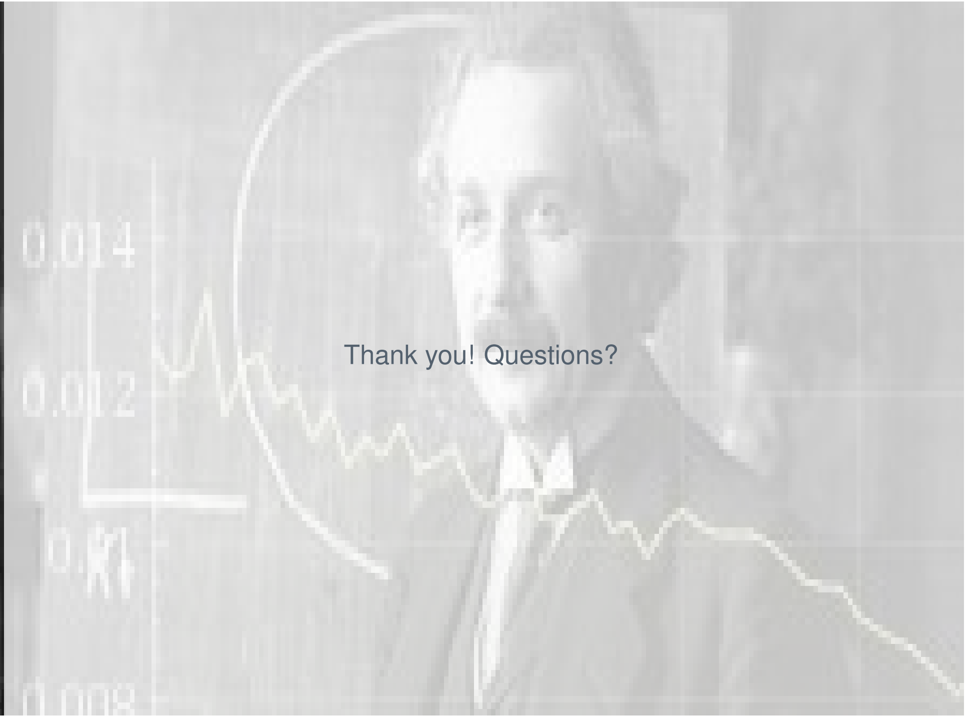

Thank you! Questions?